

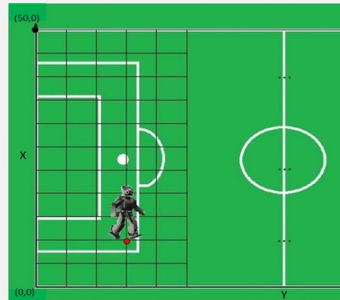
# Localization | Research Purpose

## Research Introduction

- ❖ Robots need autonomous decision-making for self-driving, requiring **robot localization**.
- ❖ Only using kinematic inputs aren't reliable due to significant errors like grass texture and robot joint backlash.
- ❖ Incorrect position estimates can lead to major mistakes, such as scoring own goals.



RoboCup 2019



Localization

- ❖ Aims for an precise and **accurate localization** despite unstable walking and limited-view cameras.

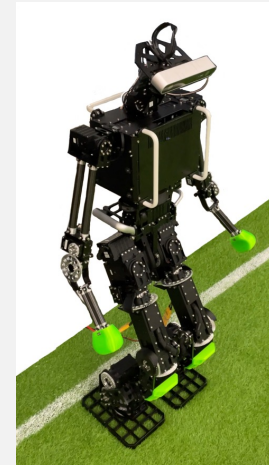
## Research Goal

- ❖ Develop an algorithm for **real-time position estimation** of the robot.
- ❖ Enable **re-estimation of position** after events like the robot falling or "kidnapping" due to collisions between robots.

## Humanoid Robot Model



ALICE in Webots



ALICE ver.3

OS : Ubuntu 20.04  
HW : Jetson Xavier, Intel NUC  
Language : Python, C/C++  
Middleware : ROS

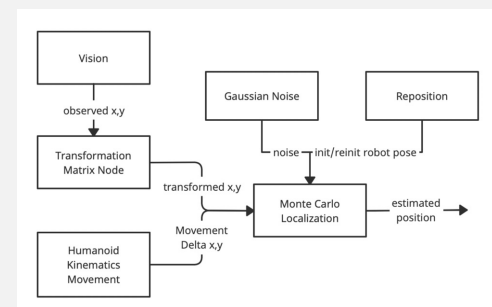
## Pseudo-code and System Diagram of Localization

### Algorithm 1 Augmented Monte Carlo Localization

**Input:**  $\chi_{t-1}, u_t, z_t, m$   
**Output:**  $\chi_t$

```
1: static  $\omega_{slow}, \omega_{fast}$ 
2:  $\tilde{\chi}_t = \chi_t = \emptyset$ 
3: for  $m = 1$  to  $M$  do
4:    $x_t^{[m]} = \text{sample\_motion\_model}(u_t, x_{t-1}^{[m]})$ 
5:    $\omega_t^{[m]} = \text{measurement\_model}(z_t, x_t^{[m]}, m)$ 
6:    $\chi_t = \tilde{\chi}_t + (x_t^{[m]}, \omega_t^{[m]})$ 
7:    $\omega_{avg} = \omega_{avg} + \frac{1}{M} \omega_t^{[m]}$ 
8: end for
9:  $\omega_{slow} = \omega_{avg} + \alpha_{slow}(\omega_{avg} - \omega_{slow})$ 
10:  $\omega_{fast} = \omega_{avg} + \alpha_{fast}(\omega_{avg} - \omega_{fast})$ 
11: for  $i = 1$  to  $M$  do
12:    $idx = \text{resampling}(\omega)$ 
13:   if  $\max(0.0, 1.0 - \omega_{fast} / \omega_{slow})$  then
14:     add random pose to  $\chi_t$ 
15:   else
16:      $idx = \text{resampling}(\omega)$ 
17:     add  $x_t^{[idx]}$  to  $\chi_t$ 
18:   end if
19: end for
20: return  $\chi_t$ 
```

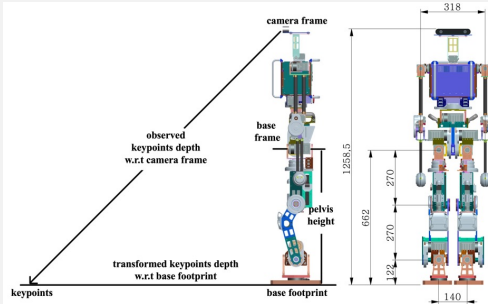
### Pseudo-code



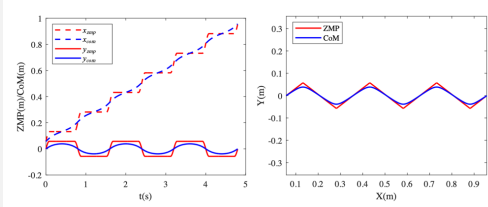
Localization System Diagram

# Localization | aMCL-based localization w/ using Object Detection Model

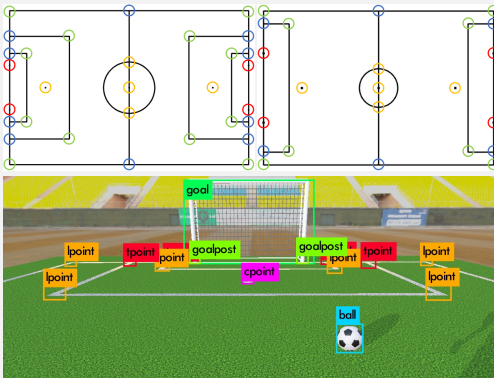
## Humanoid Localization Process



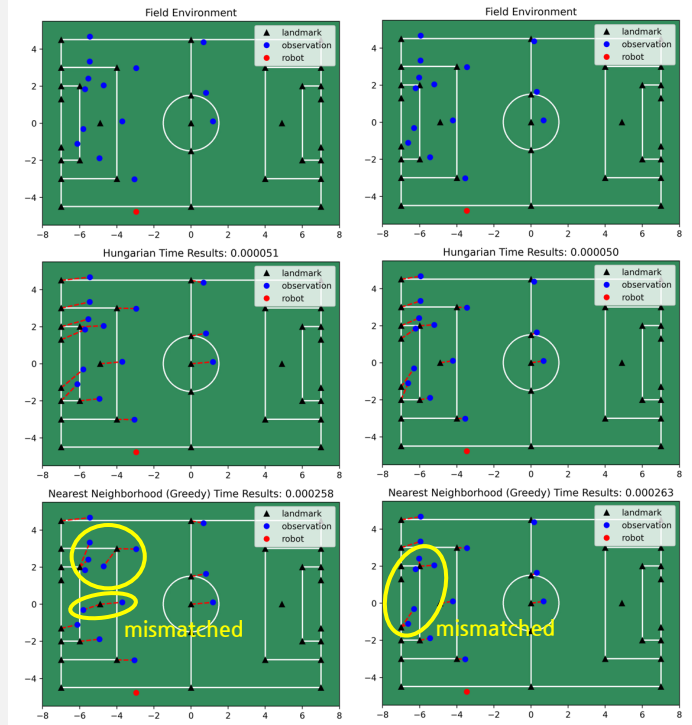
Humanoid "ALICE3", hardware and TF configuration



(1) Preview Control-based Pelvis and ZMP trajectory



(2) Detection result of pre-defined landmarks



(3) Comparison result of data association method (Hungarian algorithm and nearest neighbor method)

index	Success Rate (nearest)	Success Rate (hungarian)
scene 1	80.89%	<b>90.00%</b>
scene 2	84.25%	<b>92.01%</b>
scene 3	83.98%	<b>93.22%</b>
scene 4	85.90%	<b>96.85%</b>

Data Association evaluation of each methods

### Algorithm 3: Proposed Roulette Wheel Resampling Algorithm

```

1 Algorithm Resampling ( $\omega$ );
Input : Set of weights for each particle  $\omega$ 
Output: Set of resampled weights for each particle  $\omega_{\text{sampled}}$ 
2  $\omega_{\text{sampled}} = \emptyset$ 
3  $idx = \text{integer number of } \text{rand}() * M$ 
4  $\beta = 0.0$ 
5  $\omega_{\text{max}} = \max(\omega)$ 
6 for  $i \leftarrow 0$  to  $M$  do
7    $\beta = \beta + \text{rand}() * 2.0 * \omega_{\text{max}}$ 
8   while  $\beta > \omega^{idx}$  do
9      $\beta = \beta - \omega^{idx}$ 
10     $idx = (idx + 1) \% M$ 
11  end
12  add  $\omega^{idx}$  to  $\omega_{\text{sampled}}$ 
13 end
14 return  $\omega_{\text{sampled}}$ 

```

$$\omega(x) = \prod_{k=1}^K \omega(x)$$

(4) 파티클 가중치 계산

### (5) Pseudocode of Roulette Wheel Resampling



(6) Weigh tracking results

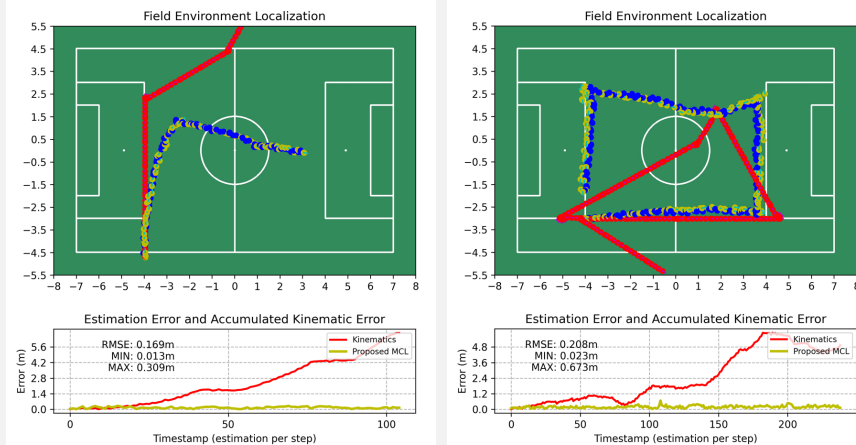
- 1) Constructing a **motion model** for prediction ( ZMP trajectory )
- 2) Creating a **sensor model** for estimation ( Deep learning-based object detection )
- 3) **Data assignment** between keypoints and landmarks ( Hungarian method )
- 4) Particle sample **weights calculation** ( Multi-variant Gaussian function )
- 5) **Resampling** for the next prediction ( Roulette Wheel )
- 6) **Tracking short- and long-term weights** to address the Kidnap problem

# Localization | Results and Performance Evaluation

## Simulation Results

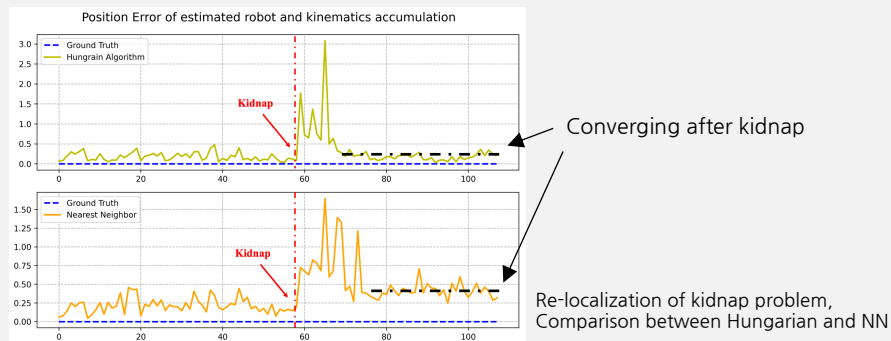
- ❖ Precise **position estimation** in noisy environments like soccer fields.
- ❖ Application of **Hungarian method** and **deep learning-based object detection** for real-time use.

■ Ground Truth ■ Estimated position ■ Kinematics position (error)



The localization results from two tested scenarios in a simulated environment

### ❖ Addressing "kidnap" problem

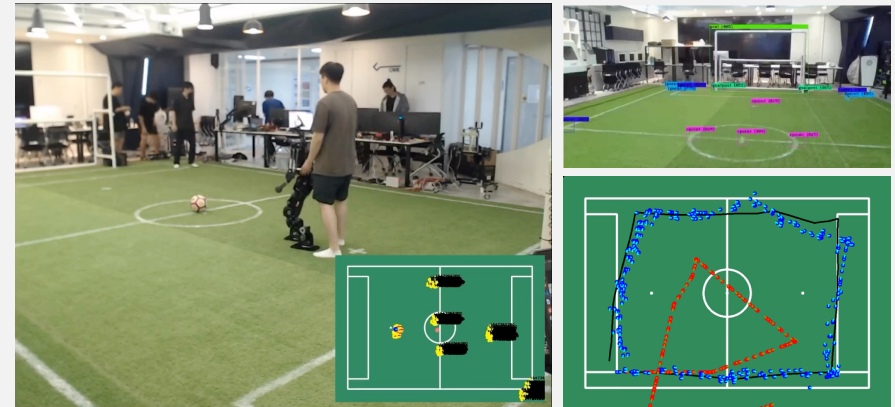


Converging after kidnap

Re-localization of kidnap problem, Comparison between Hungarian and NN

## Real-World Experiments

■ Ground Truth ■ Estimated position



Real-World localization in fully autonomous robot plays Soccer

Detection & Localization Result

## RoboCup 2022 Bangkok Humanoid AdultSize Competition



RoboCup 2022 Bangkok



RoboCup AdultSize 2nd Place



Selected news article